Tanzania Journal of Science 45(3): 315-329, 2019 ISSN 0856-1761, e-ISSN 2507-7961

Land Cover Change Detection in the Urban Catchments of Dar es Salaam, Tanzania using Remote Sensing and GIS Techniques

Philip Mzava[1*], Joel Nobert[2] and Patrick Valimba[2]

[1]*Department of Water Resources Engineering, Water Institute, P. O. Box 35059, Dar es Salaam, Tanzania.*

[2]*Department of Water Resources Engineering, College of Engineering and Technology, University of Dar es Salaam, P. O. Box 35131, Dar es Salaam, Tanzania.*

*E-mail addresses: *pmzava@gmail.com; pvalimba@yahoo.com; njoelk@yahoo.com*

**Corresponding author*

Abstract

In this study, the Maximum Likelihood (ML) classification, Normalized Difference Vegetation Index (NDVI) and Artificial Neural Network (ANN) methods were applied to three (3) Landsat images collected over time (1979, 1998 and 2014), that contained historical land cover features for the urban catchments of Dar es Salaam. Five major land cover classes were identified, mapped, and the land cover changes investigated. The major land cover changes observed from post-classification comparisons of the classified images are: the forest land losing 17.09% of its area in the period 1979-1998 to other land covers, mainly turning to grassland, and from 1998 to 2014, 17.55% of the total study area turned to high and medium/low-density built-up areas. Growth in urban settlement and infrastructure was observed to be continuously increasing and the high and medium/low-density built-up areas are projected to cover 66.09% of the total area by 2030; this is an increment of 29.01% from 37.08% coverage in 2014. This shift in land cover was further validated by the results of the Normalized Difference Vegetation Index (NDVI) analysis which showed a similar trend (shift from thick vegetation towards barren land) from 1998 to 2014, with median NDVI values changing from 0.52 to 0.36 respectively. These land cover changes are most likely the results of activities related to the increase in total population, the influx of urban population and the growth of the economy.

Keywords: Maximum Likelihood, NDVI, Artificial Neural Network, Landsat, QGIS.

Introduction

Land use refers to the varied uses of the land by human activities on the earth. What covers the surface of the earth (unaltered surface) is termed as land cover (Islam et al. 2016). How land cover is changed with time can also be used to describe land use. Detection of land use and land cover changes is useful for different purposes, including: observation of cultivation shifts, landscape changes, land degradation, deforestation, desertification, urban sprawl and quarrying activities (Gao and Liu 2010, Wyman and Stein 2010, Serra et al. 2008). In general, better management of earth resources and finding solutions to environmental problems can be achieved by understanding the interactions and/or relationships between natural and human phenomena. One way of achieving this is by observing and mapping changes in the features of the earth in an accurate and timely manner (Das 2009). Singh (1989) defined land cover change detection as temporal observation and identification of differences in the state of a feature or phenomenon.

It is approximated that about half of the world's population lives in urban areas (UN-HABITAT 2009). This proportion is expected to increase up to around 70% by 2050. In Tanzania, the urban population is estimated to be 29.6% of the country's total population (National Bureau of Statistics 2014). Although this percentage might appear small, this urban population is concentrated in the only few major cities of Tanzania, including Dar es Salaam, Mwanza, and Arusha. This indicates that the population density in these cities is very high, which is likely to bring human-induced land use and land cover changes that will subsequently alter urban watersheds ecosystem locally and slowly spread to affect the global environment (Sankhala and Singh 2014). Monitoring of land use and land cover changes is therefore very crucial for natural resources and environmental management in general, but more specifically for urban environments in developing countries like Tanzania. This is because they experience the highest rates of urbanization, with rapid increase of urban population, high population density, unplanned expansion of urban communities and the probable adverse effects these characteristics bring with, including loss of vegetated land and increased runoff and flooding, decreased water quality, increased air temperature, increased atmospheric carbon dioxide and decreased air quality (Alves and Skole 1996).

Dar es Salaam is the largest commercial, industrial and urban center of Tanzania. Its population growth has been exponential (Casmiri 2008), from a population of 83,844 in 1950 to currently over five million people. According to Wenban-Smith (2014), between 1967 and 1978 the annual rate of population growth of Dar es Salaam averaged 9.88%. This unprecedented growth characterized by unplanned and informal settlements led to urbanization with no infrastructural facilities. The city has one of the highest proportions; about 70%, of informal settlement households in East Africa (UN-HABITAT 2008). This has had serious implications on the environment. UN-HABITAT (2009) reported illegal logging aimed at charcoal making as one of the human activities that contribute to the destruction of the natural rainforests, which leads to deforestation and soil erosion in Dar es Salaam and Coastal regions.

Due to broad improvement in satellite-based technologies, Remote Sensing (RS) and Geographic Information System (GIS) have proved to be quite useful for the detection and mapping of land use and land cover patterns and changes with time (Mallick et al. 2008, Raghuvanshi et al. 2015). This is because of the reliability in data acquisition (past, recent and in a continuous manner) and format suitability for computer processing of the remotely sensed satellite images, even if the resultant spatial datasets are of different scales/resolutions (Sarma et al. 2001). Convenience in data processing, visualization and mapping are made possible with GIS technology. Therefore, these technologies are considered timesaving, cost-effective, accurate and reliable (Yang and Liu 2005). In addition, remote sensing techniques provide a basis for projecting future land cover by characterizing past land cover changes and trends from the satellite images. From the varieties of earth observing satellite programs currently in operation, Landsat program is considered unique and one of the best for change detection studies because of free availability of high-quality satellite imagery data continuously available over the past three decades.

The need to address the anticipated land cover changes has led to modeling of land cover becoming a crucial aspect of land cover change investigation. With the current availability of data and sophisticated technologies, the prediction of future land cover trends can now be done (Beaumont and Duursma 2012). Some of the most commonly used models for future land cover prediction are: Cellular Automata (Araya and Cabral 2010), Markov Chain (Guan et al. 2011), Artificial Neural Network (Schneider and Pontius 2001), and Binary Logistic Regression (Zeng et al. 2008). Because of its much wider and successful applicability in recent years over the other models, the Artificial Neural Network model was utilized in this study.

Previous studies related to land use and land cover changes investigation in Dar es Salaam region have focused mainly on studying past trends in land cover changes (Congedo and Munafò 2012), and identification of the major drivers of land cover changes (Kombe 2005). Kironde (2006) identified regulatory framework and administrative procedures that take too long to provide official ownership of land to the land seekers as one of the causes of the rapid growth of unplanned settlements in Dar es Salaam. Kombe (2005) suggested that unregulated peri-urban land development as a factor for horizontal expansion of complex urban structures in the region. This study attempts to predict future land cover change scenario and assess trends in the land cover change based on the historical Landsat images. The significance of this study is based on the fact that understanding the probable future land cover scenarios provides knowledge that will help in developing strategies and policies for better planning and management of urban growth.

The objectives of this study were: (1) to identify the past 36-year trend in land cover changes in the urban catchments of Dar es Salaam, (2) to determine the drivers of land cover changes, (3) to predict the land cover scenario of the study area for the year 2030, and (4) to produce land cover data to be used for a further study of watershed responses to changing climate and land cover in this urban environment.

Materials and Methods

Description of the study area

This research was carried out in the selected 1200 km^2 study area which is located within Pwani and Dar es Salaam regions in the eastern coastal part of Tanzania, between longitudes 39˚01'18.37" – 39˚28'29.55" E and latitudes 6˚35'17.48" – 6˚59'18.92" S. The area consists of Msimbazi (265.5 km^2), Kizinga (247.1 km^2), and Mzinga (686.4 km^2) sub-catchments. It starts from the highlands of Pwani region, running through the central urban portion of Dar es Salaam region, and draining the water into the Indian Ocean (Figure 1).

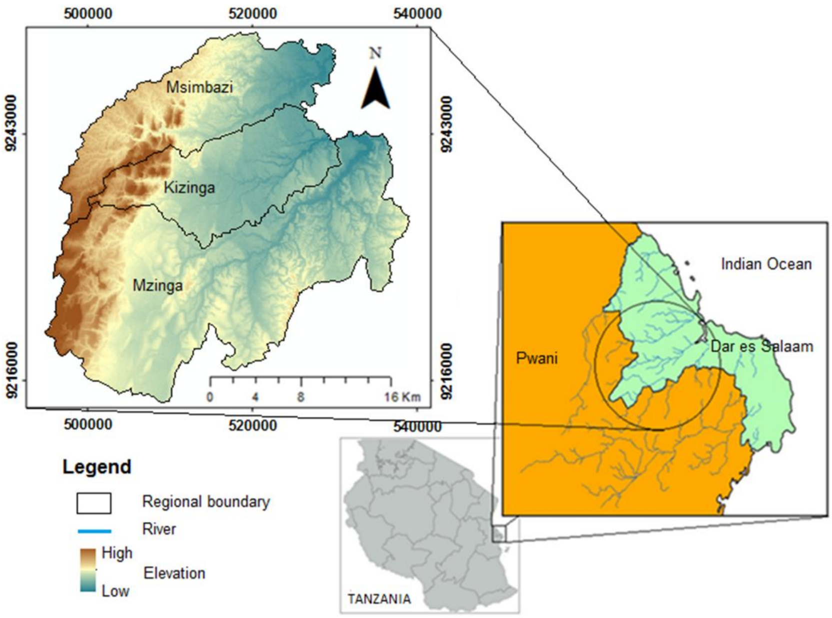

Figure 1: Location of the study area.

Within the study area, the highlands of Pwani are approximately 240 m above sea level, with a peak altitude of 339 m, and receive an average of 1200 mm of rainfall annually. The low lands of Dar es Salaam region are approximately 57 m above sea level, with the lowest altitude of 15 m, and receive an average of 1000 mm of rainfall annually. The area has a bi-modal rainfall distribution, the two main rainy seasons being the long rains and the short rains. The long rainy season ("Masika") occurs from mid-March to end of May and the short rainy season ("Vuli") from mid-October to late December. The study area is characterized by the tropical climatic conditions. It is generally hot and humid throughout the year with mean daily temperatures ranging from 26 °C during the coolest season (June-September) to 35 °C during the hottest season (October to March) (Mahongo and Khamis 2006).

Being the largest commercial, industrial and urban center of Tanzania, Dar es Salaam plays major roles in the country's economic development, contributing to about 16% of the country's Gross Domestic Product (GDP). The major economic activities around the area include tourism, fishing, forestry, mining and quarrying, and manufacturing. With a fast-growing population and rapid urbanization, the study area has the highest population density in the country, with a density of 3,133 people per square kilometer, and about 70% of the total population living in unplanned areas. These phenomena represent the most fundamental dynamic factors behind most of the immediate causes of environmental degradation (Kebede and Nicholls 2011).

Data acquisition

Satellite images freely downloaded from the United States Geological Survey (USGS) Earth Explorer Database (https://earthexplorer.usgs.gov/distribution) were used in this study. This source was chosen because it is the only one with enough temporal satellite imagery data to cover the 36-year analysis intended in this study. Three sets of temporal Landsat satellite images, including: Multispectral Scanner (MSS), Thematic Mapper (TM), and Operational Land Imager (OLI/TIRS) of 1979, 1998 and 2014, respectively, were obtained and used to investigate land cover changes in the study area from 1979 to 2014, i.e., 36-year analysis. The images were selected so that the land cover changes can be calculated approximately after every 18 years. The criterion of the percentage of cloud cover of < 10% was used to ensure cloud-free images as best as possible. Also, images between months of May to early August were used to ensure uniformity during a leaf-full season for the investigation. This was also important so as to be able to accurately compare the NDVI differences. The details of the satellite imagery data used in this study are presented in Table 1. Each remotely sensed image is comprised of different bands which had to be merged together in sets of three or more bands to form different identifiable color composites (e.g., false color, natural color, etc.). Different band combinations make it easier to identify different features based on their reflectance properties. Archived topographic map of the study area of 1980 and the Google Earth images of corresponding month and year as the Landsat images of 1998 and 2014 were used as reference data for validation of land cover classification. The reference data was used as a replacement for actual field ground proof data due to temporal discrepancy between Landsat data and the analysis.

Table 1: Details of satellite imagery data used in this study

Year	Date-Month	Path/Row	Satellite	Sensor	Spatial Resolution	Original Bands	Data Source
1979	10-Aug	178/65	LANDSAT 2	MSS	60 m	2,3,4,5	USGS
1998	16-May	166/65	LANDSAT 5	TM	30 m	1,2,3,4,5,6,7	USGS
2014	13-Jun	166/65	LANDSAT 8	OLI/TIRS	30 m	1,2,3,4,5,6,7,9	USGS

Landsat image classification, analysis, and change detection

Prior to classification and change detection, image pre-processing was performed to improve the quality of the acquired satellite images. This was achieved using the Semi-Automatic Classification Plugin (SCP) of the QGIS 2.10.1 software. Image clipping, conversion to reflectance, and atmospheric corrections were performed to the 1979, 1998, and 2014 Landsat images. Images were not radiometrically corrected or normalized since this is not a necessary step when using post-classification comparison method (Warner and Campagna 2009). Image enhancement was done to improve visual interpretability of the images. This was achieved using the histogram equalization technique. The acquired Landsat imagery data (Table 1) covering the study area were then subjected to visual inspection and interpretation. Five (5) major land cover classes were identified from the images, including forest land, grassland, bare land, medium/low-density built-up area and high-density built-up area. The built-up areas include residential areas, shopping facilities, business centers, industrial areas, and paved areas (tarmac roads and parking lots). Forest land is characterized by thick green vegetation, while grassland contains light green vegetation. Bare land is characterized by lack of vegetation with clear exposed soil.

After image interpretation and identification of the major land cover classes, digital image processing was done using the SCP plugin of the QGIS 2.10.1 software. Supervised classification (Maximum Likelihood (ML)) method was applied for classification of the Landsat images and to develop the land cover maps. This method was selected based on its wide applicability, also because the training process does not need extended time. A detailed description of the ML method can be found in the literature by Otukei and Blaschke (2010). ML is based on the Bayesian Equation (1) (ERDAS 1999), that computes the likelihood, D (weighted distance) of unknown measurement vector, *X* belonging to one of the known classes, *c*, as follows:

$$D = ln(a_c) - [0.5\ln(|Cov_c|)] - [0.5(X - M_c)\ T\ (Cov_c - 1)\ (X - M_c)] \qquad (1)$$

where: D is the likelihood (weighted distance); *X* is the measurement vector of the candidate pixel; *c* is a particular class; M_c is the mean vector of the sample of class *c*; Cov_c is the covariance matrix of the pixels in the sample of class *c*; $|Cov_c|$ is the determinant of Cov_c; Cov_c -1 is the inverse of Cov_c; T is the transposition function; a_c is the percent probability that any candidate pixel is a member of class *c*; *ln* is the natural logarithm function.

During the validation of land cover classification, a different set of data was collected apart from the data used for training of the ML classification. Based on archived topographic map and high-resolution images from Google Earth, the polygons of regions of interest were digitized (covering the whole study area) and used as reference data for validation. Using the rasterized reference data and the classified land cover maps, validation of classification was done by comparing pixel count and distribution for every land cover class. This was accomplished using the Molusce plugin of the QGIS 2.10.1 software. Two measures were used to assess the accuracy of classification, namely, the overall classification accuracy and the kappa statistic.

Post-classification comparison of the resulting land cover maps was done to examine the extent, location, and distribution of land cover changes in the study area. Annual land cover change rate was obtained using the following formula (Puyravaud 2003):

$$r\,(\%) = ([\,ln\,(A_{t2}) - ln\,(A_{t1})] \,/\, (t_2 - t_1)) \times 100 \quad (2)$$

where: A_{t1} = total area of land cover class at t_1;
A_{t2} = total area of land cover class at t_2;
t_1 = time at t_1 (preceding time);
t_2 = time following t_1 (succeeding time); and
ln = natural logarithm function.

Normalized difference vegetation index

Normalized Difference Vegetation Index (NDVI) is an indicator of the availability of live green vegetation (Rouse et al. 1973). This widely used vegetation index can also be used to quantify the growth of urban settlements and infrastructure by observing the reduction in green vegetation over time. The NDVI index values range from -1 to 1, with the scale ranging from non-vegetative (lowest value) to healthy vegetation cover (highest value). NDVI values of less than -0.1 indicate the availability of water. Values from -0.1 to less than 0.2 indicate barren land (i.e., surfaces with little to no infiltration). Values from 0.2 to 0.4 correspond to shrubs and grasslands, while values between 0.4 and 1 represent dense vegetation and forests.

An algorithm was developed using the *R* programming language for calculating and plotting the NDVI values, using the bands from satellite images that are more sensitive to vegetation information, i.e., visible red and near-infrared bands. Detection of vegetation using NDVI is based on the principle of high absorptivity of chlorophyll (vegetation pigments) in the red spectrum and high reflectance in the near infrared spectrum. The bigger the difference between red and near-infrared reflectance, the more vegetation there is. The NDVI was calculated as:

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}) \quad (3)$$

where: NIR is the near-infrared reflectance, and RED is the visible red reflectance band. The NIR and RED bands are band 4 and band 3, respectively for TM sensor, while for the OLI sensor, the NIR band is band 5, and the RED band is band 4.

Projection of land cover

Modeling of land cover in this study was done using the Artificial Neural Network (ANN) model, also known as Multi-Layer Perceptron. The past two land cover maps (i.e., 1998 and 2014) were used as reference/training data for simulating future land cover scenario of equal time span (i.e., 16-year projection). The Molusce plugin of the QGIS 2.10.1 software was used to perform the ANN modeling. Using Back Propagation (BP) algorithm, the remotely sensed image classification is undertaken through the ANN classifier. Elevation and slope data were used as control/driver spatial variables. The driver variables were used as the independent variables, while land cover change images of 1998 and 2014 were used as the dependent variables. ANN first calculates the pixels of land cover classes based on persistence and change, and it also calculates transitional probabilities. Then it calculates the trend of change and the persisted changed pixels of different land cover classes. Half of the changed pixels are taken for the training of the ANN and the remaining half for the validation purpose. The input images of 1998 and 2014 together with the calculated transitional probabilities were used to produce the simulated 2030 land cover map.

Results and Discussion

Land cover changes

The land cover maps of the study area for 1979, 1998 and 2014 derived from the supervised classification of the Landsat images are shown in Figure 2 (a, b and c). Before using the classification results from satellite images for further analysis, the validity of classification was tested against the reference/ground truth data. The 1979 land cover map had an overall classification accuracy of 76.62% and kappa statistic of 0.76. The 1998 land cover map had an overall classification accuracy of 71.79% and kappa statistic of 0.6, while the 2014 land cover map obtained 75.72% overall accuracy and kappa statistic of 0.69. The classification accuracy for each land cover class is listed in Table 2. With an average kappa index of 0.7, the produced land cover maps can be rated as good.

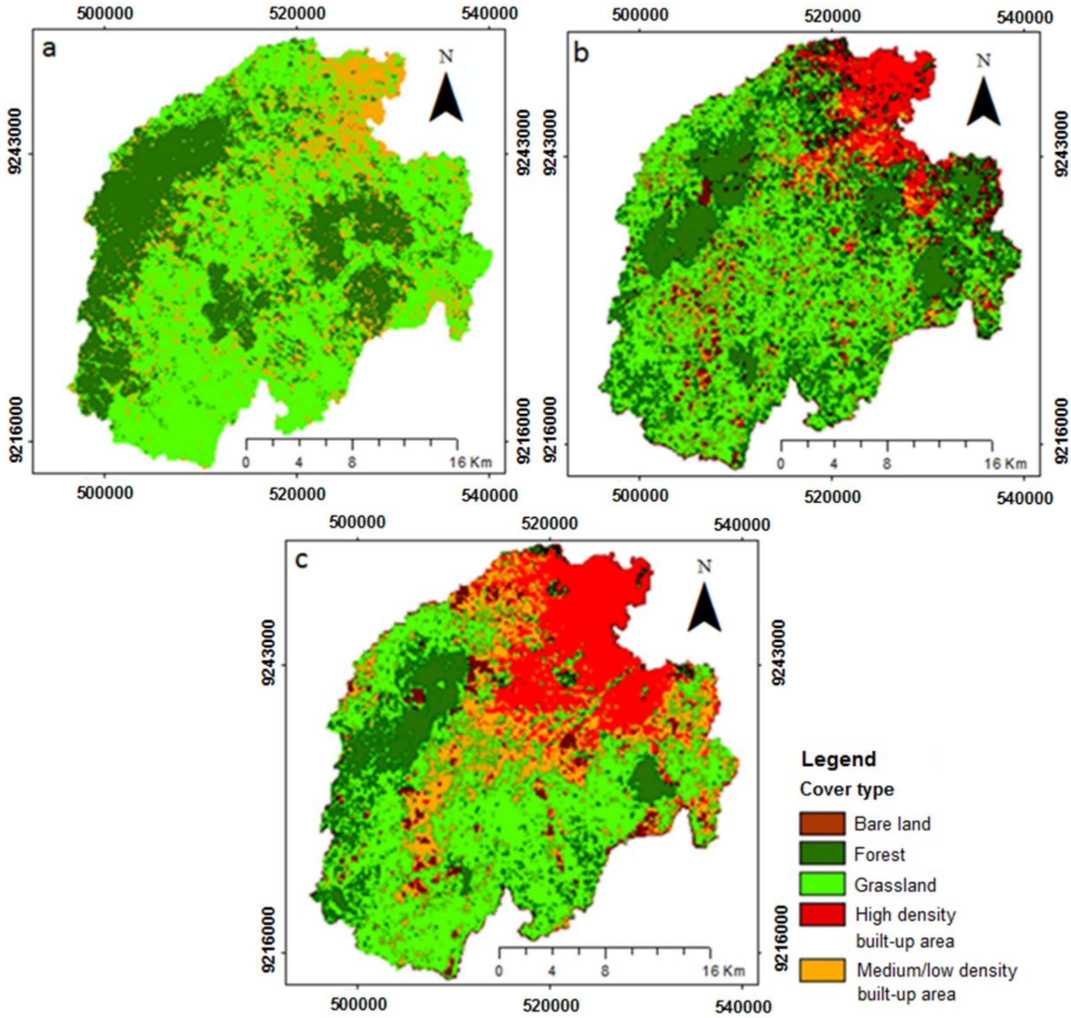

Figure 2: Land cover maps of the study area for (a) 1979 (b) 1998 and (c) 2014.

Table 2: Overall classification accuracy and kappa index statistics

Land cover class	Land cover validation accuracy		
	1979	1998	2014
Bare land	-	69.46	31.61
Grassland	88.4	76.85	86.3
Forest	62.06	44.78	83.01
Medium/low density built-up area	79.41	81.03	95.66
High density built-up area	-	86.81	82.03
Overall accuracy (%)	76.62	71.79	75.72
Kappa index	0.76	0.6	0.69

The analysis of land cover changes showed a 17.09% reduction in forest cover from 1979 to 1998, while medium/low and high-density built-up areas increased by 8.06% and 7.71%, respectively. According to the official census of 1978, the population of Dar es Salaam was 769,445. The population reached approximately 2,272,483 in the year 2000. This is equivalent to a 195.34% increase in population from 1978, with an average of 8.5% annual rate of population growth. Therefore, these land cover changes were most likely the results of mass migration from rural areas to the cities (of which Dar es Salaam was the only major city back then) that ensued after the nation's independence, and the declaration of Socialism and Self-Reliance Policy (famously known as the Arusha Declaration) of 1967. Majority of the population was seeking employment in the industrial sector, better education for their children and generally looking for better living standards and life in urban areas.

From 1998 to 2014, grassland cover was reduced by 16.04%, while there was a 13.02% increase in medium/low-density built-up area. The population of Dar es Salaam had reached an estimated figure of 4,896,000 people in 2014, which is a 115.45% increase from the year 2000. The high-density built-up area had increased only by 4.53%. This is because the majority of the people tend to settle in the outskirts of the city because of the lower costs of land and accommodation, as compared to the city center. Mostly, this is how rapid urbanizations happen in developing countries, which are facilitated by lack of urban planning. Table 3 shows the crucial statistics of all the land cover changes that occurred between 1979 and 2014.

Table 3: Land cover change statistics

Land cover class	Area (Ha)			% change (w.r.t Total Area)		Annual rate of change (%)	
	1979	1998	2014	1979-1998	1998-2014	1979-1998	1998-2014
Bare land	-	1,456.00	993.63	+1.25	-0.4	-	-2.39
Grassland	81,331.87	81,419.53	62,691.05	+0.07	-16.04	+0.006	-1.634
Forest	31,003.87	11,054.47	9,771.65	-17.09	-1.1	-5.43	-0.77
Medium/low density built-up area	4,392.60	13,800.69	28,989.94	+8.06	+13.02	+6.03	+4.64
High density built-up area	-	8,997.64	14,282.07	+7.71	+4.53	-	+2.89

Land cover transitions

Further analysis of land cover changes was done by looking at the transitions of cover classes from 1979 to 2014 (Figures 3 and 4) based on the transition matrices. This gave a more detailed picture of the parcels of land that were transformed from one class to another. It was observed that a big portion of forest land was transformed to grassland between 1979 and 1998. Due to a surge of population during this period, the lost forest land was most likely due to illegal logging for the purpose of charcoal production and/or family scale (subsistence) farming practices. Efforts to restore the destroyed hectares of forest land were observed to be partly successful during the 1998-2014 period. Although the percent change in grassland cover was very minimal during the 1979-1998 period (it had increased only by 0.07%), it does not mean that this land cover was near static.

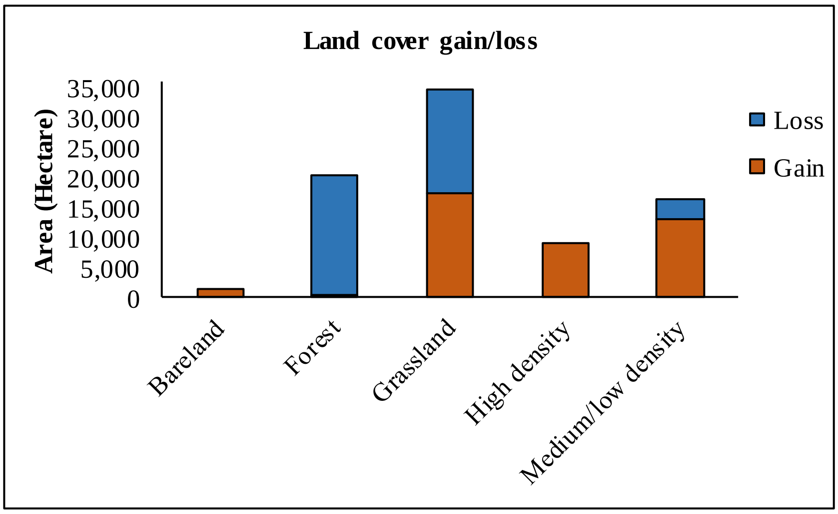

Figure 3 (a): Land cover class gains and losses between 1979 and 1998.

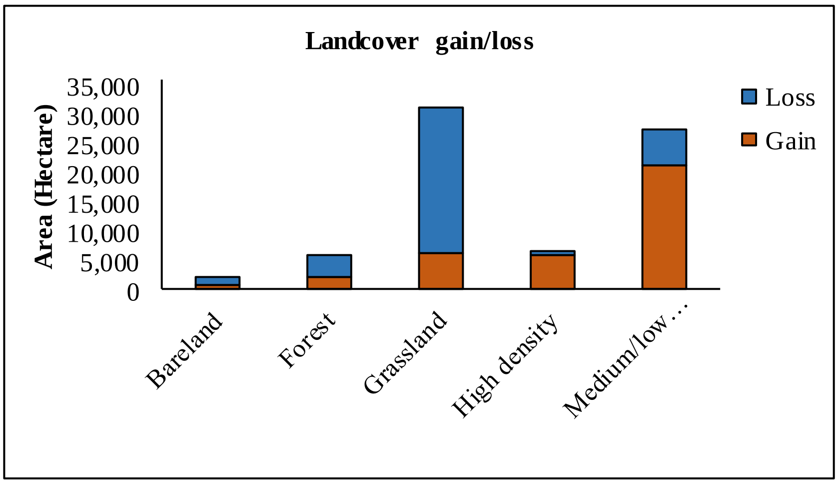

Figure 3 (b): Land cover class gains and losses between 1998 and 2014.

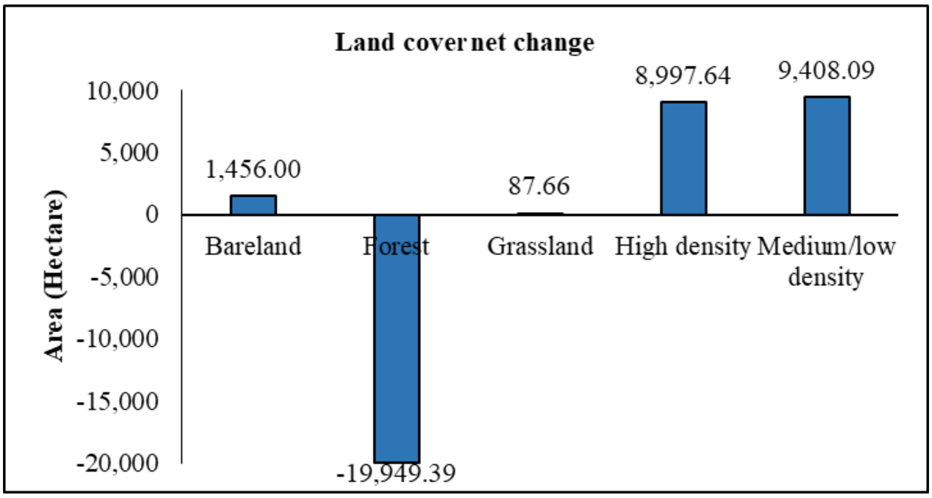

Figure 4 (a): Land cover class net change between 1979 and 1998.

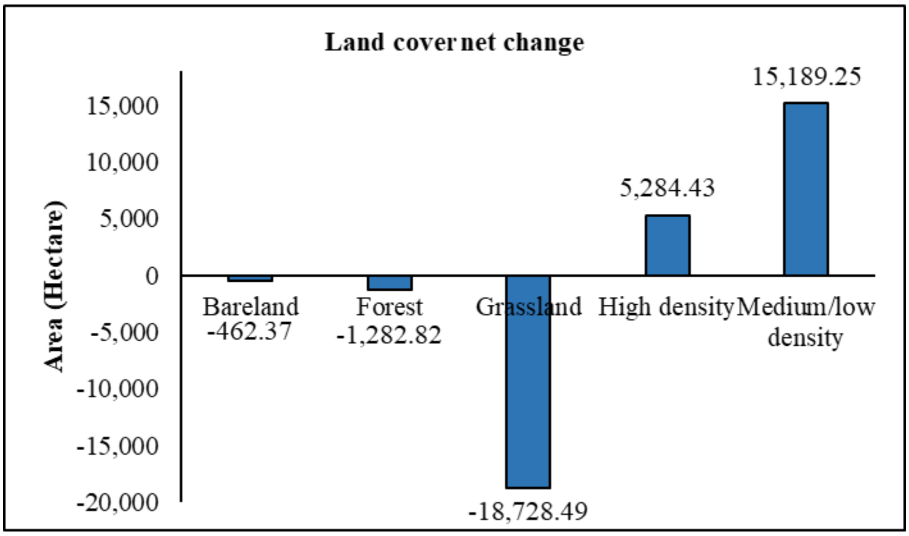

Figure 4 (b): Land cover class net change between 1998 and 2014.

It can be seen from Figure 3 (a) that grassland had gained almost the same hectares of land from forest cover as it had lost to medium/low and high-density built-up covers. That is why the net change of grassland was very small (Figure 4 (a)) but this land cover was very dynamic during the 1979-1998 period.

The transformation from grassland to medium/low-density built-up area was observed to be the major land cover transition from 1998 to 2014. Medium/low-density built-up cover had moved from occupying 11.82% of the total land to occupying 24.84%. Due to the rapid population increase and the influx of urban population, people have a tendency to search for cheaper land and accommodation in the periphery of the city. Grassland cover had lost 16.04% of its land, but still occupied

53.71% of the total land in 2014. This is largely because of the uninhabitable highlands on the western part of the study area which occupies most the forest land and a big portion of the grassland.

Normalized difference vegetation index values

NDVI values were calculated from satellite imagery data of 1998 and 2014. Satellite image from 1979 could not be used for the analysis of NDVI due to lack of required bands for NDVI calculation. To better understand the land cover transitions between 1998 and 2014, NDVI values were classified into different categories representing different features as described previously. NDVI values were plotted as histograms (Figure 5) in order to understand the general land cover transition over time. From Figure 5, it can be observed that the shape of the histogram is shifting from being highly skewed in the high positive values of NDVI (with a median value of 0.52) in 1998, towards being near normally distributed around values approaching zero (with a median value of 0.36) in 2014. This indicates a shift from dense vegetation towards grassland and barren land. This shift can also be visualized from the mapped values of NDVI in Figure 6. These results further validate the land cover change results obtained from the first analysis.

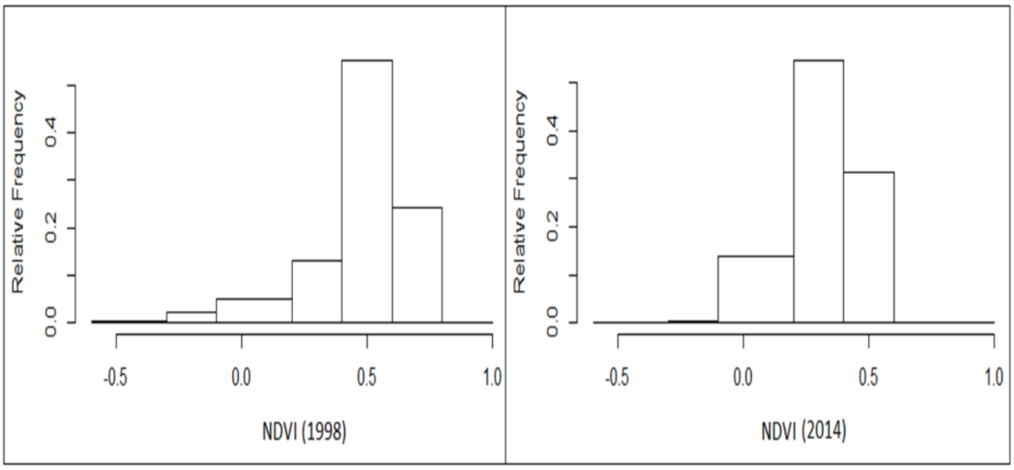

Figure 5: NDVI relative frequencies for 1998 and 2014.

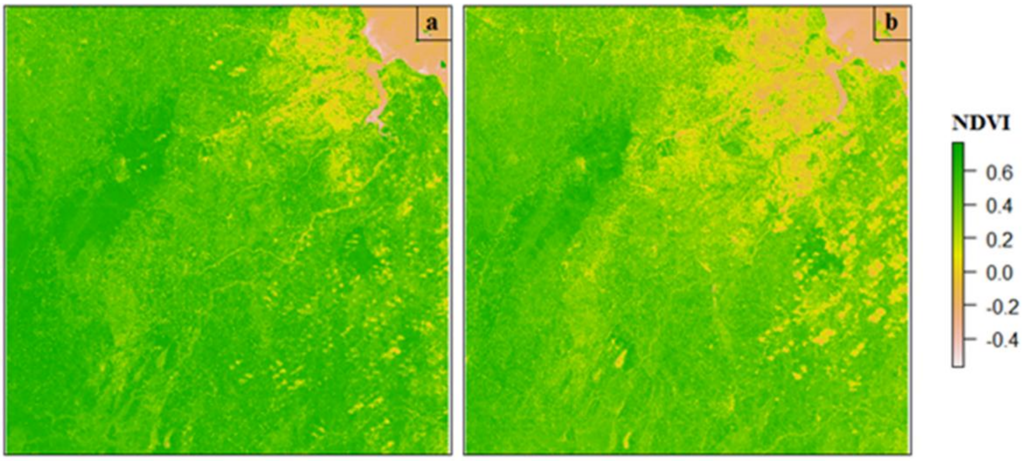

Figure 6: Graphical representation of NDVI values for (a) 1998 (b) 2014.

Projection of land cover

Projected land cover map of the study area for the year 2030 is shown in Figure 7. The analysis of land cover changes showed a further 20.32% reduction in grassland cover from 2014 to 2030, while medium/low and high-density built-up areas are expected to increase by 16.76% and 12.25%, respectively. Table 4 shows other statistics of the land cover changes that are expected to occur between 2014 and 2030. The direction of urbanization appears to sprawl outward from the original urban center, going in the south-east direction, avoiding the high altitudes on the western part of the study area. Apart from the mountainous area on the western part of the study area, which is mainly covered by grassland, the remaining part (lowland area) appears to be almost fully covered by medium/low and high-density built-up land covers—with very little grassland cover.

During this study, land cover transition analysis in the period 2014-2030 was limited to investigating the shift within same land cover class; as shown in Table 4. Analysis of the effects of change in one land cover class on other classes was not investigated in this study. Investigation of future transitions among different land covers can provide direction for future research opportunity in land cover change projection modeling in the study area.

The nature of urbanization in the study area suggests that lack of urban planning and economic status of the population play a big role in the rapid process and direction of urban expansion. This is because people tend to look for cheaper land and accommodation around the city center, business centers, industrial areas, and communication networks. This process is unrestricted and uncontrolled with the lack of urban planning. This may further result to complications such as difficulty in providing necessary services, e.g., clean water and power supply, drainage and road networks, which may also result to increased travel time, fuel consumption, environmental pollution, etc. These problems are evident in most urban communities in Dar es Salaam. Similar characteristics and trend of urbanization in Dar es Salaam region were observed by Congedo and Munafò (2012), who reported a growing trend of new urbanization along the main roads and development of new urban areas away from the city center.

Tanzania Journal of Science 45(3): 315-329, 2019 ISSN 0856-1761, e-ISSN 2507-7961

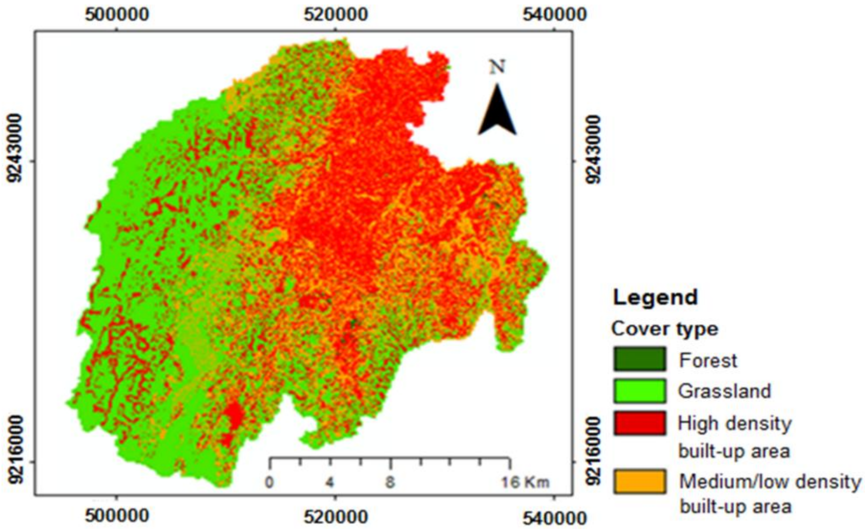

Figure 7: Simulated land cover map for the year 2030 based on ANN modeling.

Table 4: Projected land cover change statistics

Land cover class	Area (Ha)		% change (w.r.t. total area)
	2014	2030	2014-2030
Bare land	993.63	-	-0.85
Grassland	62,691.05	38,980.91	-20.32
Forest	9,771.65	598.89	-7.86
Medium/low density built-up area	28,989.94	48,560.74	+16.76
High density built-up area	14,282.07	28,587.79	+12.25

Conclusion

The usefulness of multi-temporal Landsat images in detecting land cover change was demonstrated by this study. Analysis of 36-year land cover changes in the urban catchments of Dar es Salaam was presented. According to the findings of this study, it is clear that in the past 36 years the human activities have profoundly changed the land cover of the study area. A clear shift from thick vegetation to an urban built-up environment was observed. The projected land cover map shows that the growth in the urban settlement will be continuous and about 66.09% of the total study area will consist of the built-up area by 2030; this is an increment of 29.01% from 37.08% coverage of this land cover class in 2014. These changes are most likely the results of activities related to the increase in total population, the influx of urban population and the growth of the economy.

The findings of this study may help to develop strategies and policies for better planning and management of Dar es Salaam urban growth. This may lead to increased efficiency in land use and diminish land use and land cover related negative impacts to society and the environment. Land cover maps generated from this study are also considered vital input data in a further study of watershed responses to changing climate and land cover in the same study area.

Acknowledgments
The authors appreciate the financial support from the German Academic Exchange Service (DAAD). They are also thankful to the University of Dar es Salaam (UDSM) for being the hosting institution during conducting this research.

References
Alves D and Skole D 1996 Characterizing land cover dynamics using multi-temporal imagery. *Int. J. Remote Sens.* 17 (4): 835-839.
Araya YH and Cabral P 2010 Analysis and modeling of urban land cover change in Setúbal and Sesimbra, Portugal. *Remote Sens.* 2: 1549-1563.
Beaumont LJ and Duursma D 2012 Global projections of 21st-century land-use changes in regions adjacent to protected areas. *PloS One*. 7(8): p.e43714.
Casmiri D 2008 Vulnerability of Dar es Salaam City to Impacts of Climate Change. EPMS, Dar es Salaam, p. 22.
Congedo L and Munafò M 2012 Development of a Methodology for Land Cover Classification in Dar es Salaam using Landsat Imagery. Sapienza University, Rome. Available at: http://www.planning4adaptation.eu/
Das T 2009 Land use/land cover change detection: an object-oriented approach. Institute of Geoinformatics, University of Münster.
ERDAS 1999 ERDAS Field Guide: Revised and Expanded, 15th ed. ERDAS Inc., Atlanta, GA, USA.
Gao J and Liu Y 2010 Determination of land degradation causes in Tongyu County, Northeast China via land cover change detection. *Int. J. Appl. Earth Obs. Geoinf.* 12(1): 9-16.
Guan DJ, Li HF, Inohae T, Su WC, Nagaie T and Hokao K 2011 Modeling urban land use change by the integration of cellular automaton and Markov model. *Ecol. Model*. 222: 3761-3772.
Islam K, Jashimuddin M, Nath B and Nath TK 2016 Quantitative assessment of land cover change using Landsat time series data: the case of Chunati Wildlife Sanctuary (CWS), Bangladesh. *Int. J. Environ. Geoinf*. 3 (2): 45-55.
Kebede AS and Nicholls RJ 2011 Population and Assets Exposure to Coastal Flooding in Dar es Salaam (Tanzania): Vulnerability to Climate Extremes Report. Global Climate Adaptation Partnership (GCAP) Programme.
Kironde J 2006 The regulatory framework, unplanned development and urban poverty: Findings from Dar es Salaam, Tanzania. *Land Use Policy* 23(4): 460-472.
Kombe W 2005 Land use dynamics in peri-urban areas and their implications on the urban growth and form: the case of Dar es Salaam, Tanzania. *Habitat International* 29(1): 113-135.
Mahongo SB and Khamis OI 2006 The Tanzania National Sea Level Report. Tanzania Fisheries Research Institute and Department of Survey and Urban Planning. Available online at: http://www.gloss-sealevel.org/publications/documents/tanzania2006.pdf
Mallick J, Kant Y and Bharath BD 2008 Estimation of land surface temperature over Delhi using Landsat-7 ETM +. *J. Ind. Geophys. Union* 12 (3): 131-140.
National Bureau of Statistics 2014 Basic Demographic and Socio-Economic Profile. National Bureau of Statistics (NBS), Tanzania.
Otukei JR and Blaschke T 2010 Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *Int. J. Appl. Earth Obs. Geoinf*. 12: S27-S31.
Puyravaud JP 2003 Standardizing the calculation of the annual rate of deforestation. *Forest Ecol. Manage.* 177(1-3): 593-596.
Raghuvanshi TK, Negassa L and Kala PM 2015 GIS-based Grid overlay method versus modeling approach–a comparative

study for landslide hazard zonation in Meta Robi District of West Showa Zone in Ethiopia. *Egypt. J. Remote Sens. Space Sci*. 18 (2): 235-250.

Rouse JW, Haas RH, Schell JA and Deering DW 1973 Monitoring vegetation systems in the Great Plains with ERTS. *Third ERTS Symposium, NASA*. SP-351I: 309-317.

Sankhala S and Singh B 2014 Evaluation of urban sprawl and land use land cover change using remote sensing and GIS techniques: a case study of Jaipur City, India. *Int. J. Emerg. Technol. Adv. Eng*. 4 (1): 66-72.

Sarma VVLN, Krishna GM, Malini BH and Rao KN 2001 Landuse/Landcover change detection through remote sensing and its climatic implications in the Godavari Delta Region. *J. Indian Soc. Remote Sens.* 29(1 & 2): 85-91.

Schneider LC and Pontius RG 2001 Modeling land-use change in the Ipswich watershed, Massachusetts, USA. *Agric. Ecosyst. Environ*. 85 (1-3): 83-94.

Serra P, Pons X and Saurí D 2008 Land-cover and land-use change in a Mediterranean landscape: a spatial analysis of driving forces integrating biophysical and human factors. *Applied Geography* 28(3): 189-209.

Singh A 1989 Digital change detection techniques using remotely-sensed data. *Int. J. Remote Sens.* 10(6): 989-1003.

UN-HABITAT 2008 State of the World's Cities 2008/2009 - Harmonious Cities. UN-HABITAT (United Nations Human Settlement Programme), Nairobi, Kenya. Available from: http://www.unhabitat.org/pmss/getPage.asp?page=bookView&book=2562

UN-HABITAT 2009 Tanzania: Dar es Salaam City profile. UN-HABITAT (United Nations Human Settlement Programme), Regional and Technical Cooperation Division, Nairobi, p. 36.

Warner TA and Campagna DJ 2009 Remote sensing with IDRISI Taiga: A beginner's guide. Hong Kong, Geo-carto International Centre.

Wenban-Smith HB 2014 Urbanization in Tanzania. Available from: www.theigc.org/publications/workingpaper/urbanisation-tanzania

Wyman MS and Stein TV 2010 Modeling social and land-use/land-cover change data to assess drivers of smallholder deforestation in Belize. *Applied Geography* 30(3): 329-342.

Yang X and Liu Z 2005 Use of satellite-derived landscape imperviousness index to characterize urban spatial growth. *Computers, Environment and Urban Systems* 29: 524-540.

Zeng YN, WU GP, Zhan FB and Zhang HH 2008 Modeling spatial land use pattern using autologistic regression. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XXXVII (B2): 115-118.